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Event Studies in thinly-traded markets:
An improvement to the market model

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Abstract: Whether a market is thinly traded or not, the calculation of expected returns is a necessary ingredient in data processing for an event study. The method most commonly used is the market model. This often fails to meet the OLS requirement of normally distributed residuals, and tends to furnish regression output (low R^2, and insignificant *t*- and *F*-statistics) that, in other contexts, one would not rely on. With respect to data sets fraught with thin trading, the problem is exacerbated since missing data tends usually to be proxied by zero-value returns whose rate of occurrence distorts the computation of OLS parameters. A family of models, in which company and market return relationships are separated out by dummy variables, offer improved computation of expected returns when applied to thinly-traded data sets. The best of these is a 3-state (by company) model. Abnormal returns from this model are compared with those from the market model in detecting dividend and earnings signals and are found to make a similar diagnosis.

Key Words: Event Study Research, State Asset Pricing Models, Comparative Methodology, Zero-value Returns, Thin Trading

JEL Classification: G14, G19.

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Event Studies in thinly-traded markets: An improvement to the market model

1. Introduction.

Event studies traditionally employ the market model for calculating abnormal returns that determine if a particular event's news content significantly impacts on share value or not. In a thinly-traded market context, this paper investigates whether the market model can be improved upon by the use of dummy variables modeling the direction of company price movements relative to movements in market prices more generally. Why is this a good idea? Thinness of trading may, in extreme form, entail no trades taking place over many consecutive days in an event study model's estimation period. This has the capacity to distort the parameters used in computing return expectations. Additionally, the market model's simple OLS procedure usually furnishes expected returns with a tiny R^2 statistic implying relatively low explanatory power. Intuitively, one would want expected returns, given that they are deemed to be market-risk adjusted, to be associated with R^2 statistics that are not vanishingly small.

In general event studies are used extensively and have been examined methodologically by a number of researchers. Brown and Warner (1985) considered whether or not the market model offered any improvement over the conducting of event studies in which abnormal returns are calculated by two simpler methods. The mean adjusted return approach defined an abnormal return as the difference between a company's observed return and the company's mean return over some estimation period. The market-adjusted return approach merely entailed subtracting the day's market return from the firm's observed return. These methods performed almost as well as the market model, but suffer a conceptual disadvantage in that they do not adjust for market risk.

A series of researchers from Fama and French (1993) onward, notably including Campbell and Vuolteenaho (2003), have developed equity valuation models employing regression that make use of measures of relative company size and performance. In these models, size (market value of equity) and performance (ratio of book to market value of equity) are called included. Since these are possible replacements for the market model in the event study context, Ahern (2009) assesses the Fama and French three-factor model, and Cahart's (1997) four-factor model along with the market model on NYSE data-sets and finds that all of the models exhibit significant bias, while only a characteristic-based benchmark model developed by Daniel et al (1997) performed well.

A methodology that was developed specifically for dealing with thinly-traded stocks was the trade-to-trade model of Marsh (1979), Dimson and Marsh (1983) and Maynes and Rumsey (1993). This entails dropping periods in which a firm fails to trade and calculating periodic returns from the closing prices from the no-longer-even-sized periods left in the estimation period data set. The method also requires the scaling of returns to counter heteroscedasticity induced by employing non-uniform units of time in the estimation period. Maynes and Rumsey showed that the trade-to-trade method is an effective technique when used in conjunction with a nonparametric rank test which they adapted from Corrado (1989). This method was examined in the thin-trading environment of the Copenhagen Stock Exchange by Bartholdy, Olson and Peare (2007).

Corrado's rank test, however, is not necessarily restricted in use to the trade-to-trade model. Corrado and Truong (2008) tested it out on a number of Pacific Basin stock exchanges with respect to the market model.[1] Corrado (2009) provided an overall summary of event study methodologies. The current paper, however, does not investigate the rank test because the event study example it employs looks at the simultaneous announcement of earnings and dividends, for which the measure of significance is the restricted least squares *F*-test employed by Kane, Lee and Marcus (1984), Easton (1991) and Lonie, Abeyratna, Power and Sinclair (1996).

The current paper focuses on providing a simpler alternative by investigating models based on the market model, with dummy variables controlling for the sign of company returns and of market returns. While keeping the market model's advantage of an adjustment for market risk, these offer a marked improvement on the market model's explanatory power, which makes an investigation of them enticing. Further, their regression procedures furnish larger adjusted R^2 statistics and larger, statistically more significant *F*-statistics than does the market

1 Corrado and Truong, whose investigation adopted Brown and Warner's (1985) Monte Carlo simulation approach, noted that both the Thai and Australian Stock Exchanges furnished data series in which the incidence of zero-value returns approached fifty percent. However Corrado and Truong did not address the issue of thin trading, since they excluded from their study (p. 499) any potential data selections that contained more than 50 zero-value return observations out of the 200 required to represent a firm's estimation period. In other words they restricted themselves to data that traded at least 75 percent of the time.

model, along with residuals that are more likely to conform to a normal distribution. This is especially useful because, the less often shares change owners in a company's event study estimation period, the less likely it is that the regression inputs or outputs are going to be normally distributed.

While the market model has been found by researchers such as Brown and Warner (1985) to be robust on data that is not necessarily normally distributed, models that do more closely meet the best linear unbiased estimator requirements of OLS regression must surely be attractive. Therefore this paper rates a set of candidate models on their performance in generating expected return parameters for future service in an event study, where the rating criteria are R^2 and *F*-values, and the incidence of normally distributed residuals. In particular, we are interested in how useful the models are when operating on data sets where thinness of trading is increasingly the norm.

Another method for dealing with the thin trading problem has been the development of models employing aggregated coefficients. The two leading early paper in the field were Scholes and Williams (1977), and Dimson (1979). However, Bartholdy and Riding (1994) found, on data for thinly-traded New Zealand securities, that the conventional market model produced betas that were as consistent as those of Scholes and Williams, while superior in efficiency and smallness of bias. Fowler, Rorke and Jog, (1979 and 1989); Martikainen, Perttunen, Yli-Olli and Gunasekaran, (1994) among others produced further models addressing thin trading. However, if any adjustment is made at all when dealing with data sets containing instances of zero trading observations, event study researchers have tended to make use of Scholes and Williams (1977), or Maynes and Rumsey (1993).

But the problem of missing trades still gives rise to the need for a decision on how to best deal with it. This may be a matter of grooming at the level of the raw data. CRSP, for instance, approximates missing prices in United States data according to quite a complex set of criteria. On the other hand, no data at all may be entered in some time series in place of missing trades. A third approach, used by DataStream, is simply to plug any gap in a time series with a zero-value return (lumped return method). Kallunki (1997) investigated the characteristics of the market model run on lumped method data and found that the zero-value returns in the data series gave rise to positive autocorrelation in returns, which might render the resulting abnormal returns erroneous. However, he also found that this problem could be remedied by using the model in conjunction with the standardized cross-sectional t-test developed by Boehmer, Musumecci and Poulsen (1991).

The approach taken by the current study is to modify the market model with dummy variables for the sign of company returns and of market returns. These modifications are designed for handling thin data that has been groomed by the lumped method, but leave the choice open as to what hypothesis testing methodology should be adopted.

There is a small family of possible models employing dummy variables which compartmentalize either company or market returns, or both sorts of return by whether they are positive or negative. Defining the term "state" to mean whether a return is positive or negative, the simplest model in the family is a 2-state model in which company returns that are greater than or equal to zero in value are segregated into the first state, and the second state contains company returns that are negative. second alternative 2-state model might segregate company and market return pairs likewise by the sign of the market return. A third, more cogent alternative in the context of thin trading, is a two-state model that segregates zero-value company returns from returns that are non-zero in value. But as the number of states increase, the number of basic permutations goes down. Hence there are two possible 3-state models, and only one 4-state model – ignoring permutations created by rotation or translation (which are beyond the study's purview).

Norsworthy, Gorener, Morgan, Schuler and Li (2004) set up a 4-state model which partitions daily company returns into four quadrants depending on whether they are positive or negative in conjunction with the sign (positive or negative) of the market return for the same day. Their model furnished twice the explanatory power of the conventional market model. However Norsworthy et al's purpose was quite removed from any thin-trading focus. They were looking for decision-framing effects posited by Prospect Theory (Kahneman and Tversky 1979 and 1991). Further, their study employed only 40 sets of daily returns data that were each 15 years in length.

Norsworthy et al were not the only authors to consider 4-state models. On French data, Jokung and Meyfredi (2003) investigated the basic 4-state, a rotated version and a translated 4-state model as alternative tools to the market model for event studies in general. They found all three produced a reduction in non-systematic risk and an improvement in the stability of betas. But while Jokung's and Meyfredi's time-series of daily observations at five years were only one third the length of those of Norsworthy et al, the time-series of both sets of authors were somewhat long for employment in a standard event study, of, say dividend announcements, where announcements are made as frequently as twice or even four times a year.

The models employed in the current study are a 2-state model (segregating zero-value from non-zero company returns), two 3-state models and a four-state model on data subject to various degrees of thin trading. All of these are performance-tested against the market model on the same data. But the data sets are of a more conventional length for event study purposes. The estimation period for generating expected returns is restricted to the 100 days of company log returns that precede a test period of 21 days centered about a day zero, (the day of a targeted event). There is an actual event underlying the data sets. This is a joint dividend and earnings disclosure. Although the paper furnishes the results of this event study, it does not set out to examine the nature of dividend (or earnings) signaling in anything more than a cursory manner. The primary focus is on the quality of the expected returns underlying the abnormal returns employed in such an examination. The 948 data sets used in the study are from New Zealand Stock Exchange-listed shares 1990-1999.

Of the models considered, the 3-state model with partitioning by sign of company return turns out to be the most useful. In this model, company returns are assigned to the positive region when they are positive, to the negative region when negative, and isolated from the model's dummy regression procedure when they are zero in value.

The rest of the paper is as follows. Section 2 explains the mechanics of the models; Section 3 provides a description of the data; and then Section 4 assesses the quality of expected returns with respect to the various models' regression results. Section 6 furnishes the paper's conclusions. In an appendix, abnormal returns generated from the study's expected returns are used in assessing evidence of a signalling effect of joint dividend and earnings disclosures. Here the comparison is restricted to being between the best of the state models and the market model.

2. Methodology.

The methodology used in this paper is very simple. Four models employing dummy variables are compared with the market model on an identical portfolio of data sets. The criteria for assessment are the OLS regression outputs provided by each model with respect to that portfolio. In particular, the mean recorded *F*-statistics and p-values are considered along with the R^2 statistics. In addition, the residuals for the regressions are subjected to both Jarque-bera and Liliefors tests for normality. With respect to the output of the normality tests, the data sets in the study are partitioned into bands of trading thinness. Further, because all zero-value returns have the same impact on models, zero-value returns from both liquidity-trading and from absence of trading are lumped together. This section describes the specifications of each candidate model, starting with the market model.

2.1. Market Model.

The market model is the traditional workhorse for computing a measure of reaction by investors to a given news event occurring on a known date, t_0, or over a specified number of days (event window) spanning that day. This entails the specification of the reactivity measure, which is usually an abnormal return (AR) or a cumulative abnormal return (CAR). These are calculated as a measure of how much an observed return departs from expectation as predicted by the model. Hence, a time series of closing price data is required that is long enough to furnish a span over which an expected return can be estimated (estimation period), and a portion left over (known as the test period) for comparing and contrasting observed returns relative to that expectation. If the news has an impact on investors, then investor trading activity will show up as an AR spike in the 'event window' portion of the test period, the rest of which should contain ARs that are small and insignificant.

In this study, the event window will be defined as day t_0, embedded at the centre of a 21-day test period, which is preceded by a 100-day estimation period.

The basic building blocks for the calculation of expected returns are the daily log return, R_{At} (the return on company A on day t) and the return on the market index for the same day, R_{Mt}:

$$R_{At} = \ln\left[\frac{P_{At}}{P_{At_{-1}}}\right] \tag{1}$$

$$R_{Mt} = \ln\left[\frac{Index_t}{Index_{t_{-1}}}\right] \tag{2}$$

Because closing price data series should be free of the effects of share splits and dividend payments, P_{At} characteristically comes from an index of adjusted closing prices. The expected return, $E(R_{At})$ is calculated from the parameters estimated in the OLS regression[2]:

$$R_{At} = \beta_{1A} + \beta_{2A} R_{Mt} + \varepsilon_{At} \tag{3}$$

Return expectations can be forecasted for each day (t) of the test period by applying these regression parameters:

$$E\left(R_{At}\right) = \beta_{1A} + \beta_{2A} R_{Mt} \tag{4}$$

Test period ARs and CARs are then:

$$AR_{At} = R_{At} - E\left(R_{At}\right) \tag{5}$$

And:

$$CAR_{AT} = \sum_{t=1}^{T} AR_{At} \tag{6}$$

An alternative version of CAR_{AT} is an averaged CAR which entails scaling the right-hand side of Equation (6) by $1/T$

2.2. 2- and 3-state Models.

The 2-state model is simply the market model with the zero-value returns segregated out. This is in the spirit of Brown and Warner (1985), who specified that their Monte Carlo simulation data sets for testing the market model must exclude any day on which there was no trading and the next day as well. But unlike in Brown and Warner, the segregated zero-values from non-trading still have a role to play in the model. When a period furnishes a zero-value return (from either a failure of trading or from liquidity trading only), then it is a reasonable assumption that a news event on that day has produced no response – literally no change in price. Therefore it is reasonable to equate a zero-value return with a zero value abnormal return, which does not require explicit calculation within the OLS regression procedure.

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2. The numbering of the intercept term and slope coefficient β_{1A} and β_{2A} instead of the more traditional α and β is to facilitate the scheduling the outputs of a model per column in Table 1 and later tables.

There are two possible 3-state models, both of which partition returns into a positive state, a negative one, and the third state in which returns are zero in value. This zero-value state pertains to zero-value company returns in both models. This is because the underlying purpose is to bring an adjustment for thin trading explicitly into the calculation of expected returns; and it is the absence of trading in a company's stocks that is of interest rather than the liquidity of a stock market as a whole. Aside from that, it is also unlikely that the return on the market index will ever be exactly zero unless the stock exchange happens to be extremely small with only a few dozen companies listed on it.

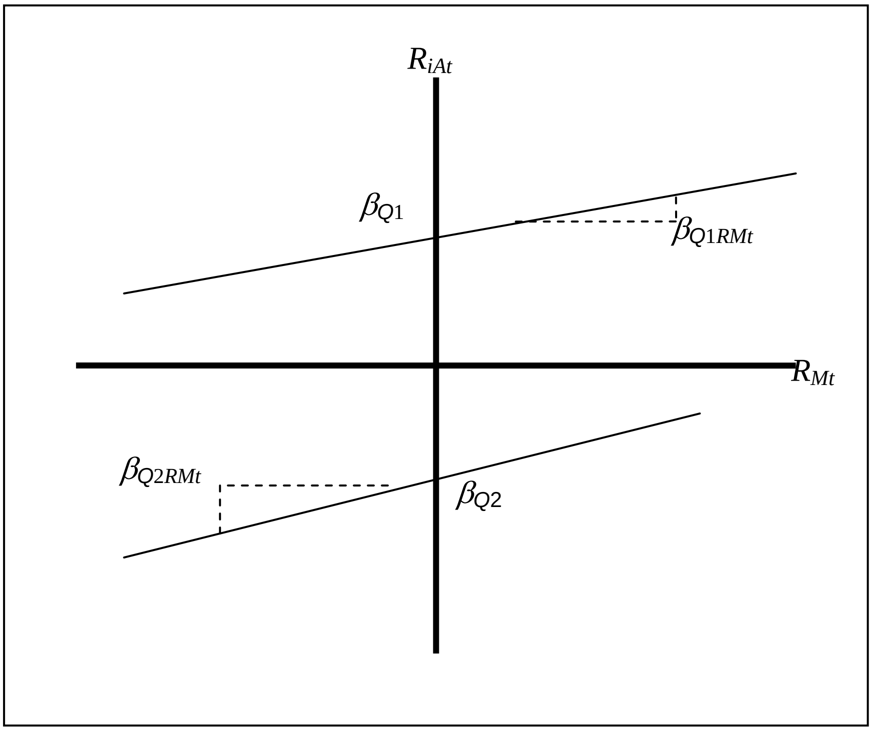
2.2.1. 3-state (by Company) Model.

The three states of the 3-state model partitioned by company depend on the sign of the returns, R_{iAt}, which can be positive, negative or neither (zero). The model employs two dummy variables. These are Q_1, which takes on the value '1' when R_{iAt} is positive and zero otherwise, and Q_2, which takes on the value '1' only when R_{iAt} is negative. $\beta_{Q1}Q_1$ and $\beta_{Q2}Q_2$ are both intercept terms.

$$R_{iAt} = \beta_{Q1}Q_1 + \beta_{Q2}Q_2 + \beta_{Q1RMt}Q_1R_{Mt} + \beta_{Q2RMt}Q_2R_{Mt} + \varepsilon_{jt} \tag{7}$$

The zero state is dropped out of the dummy regression procedure in Equation 7 on the ground that a zero company return is deemed to be both its own expected return and abnormal return. The slopes of the positive and negative company returns, as shown in Figure 1, are independent of each other.

Figure 1: 3-state (by Company) Model

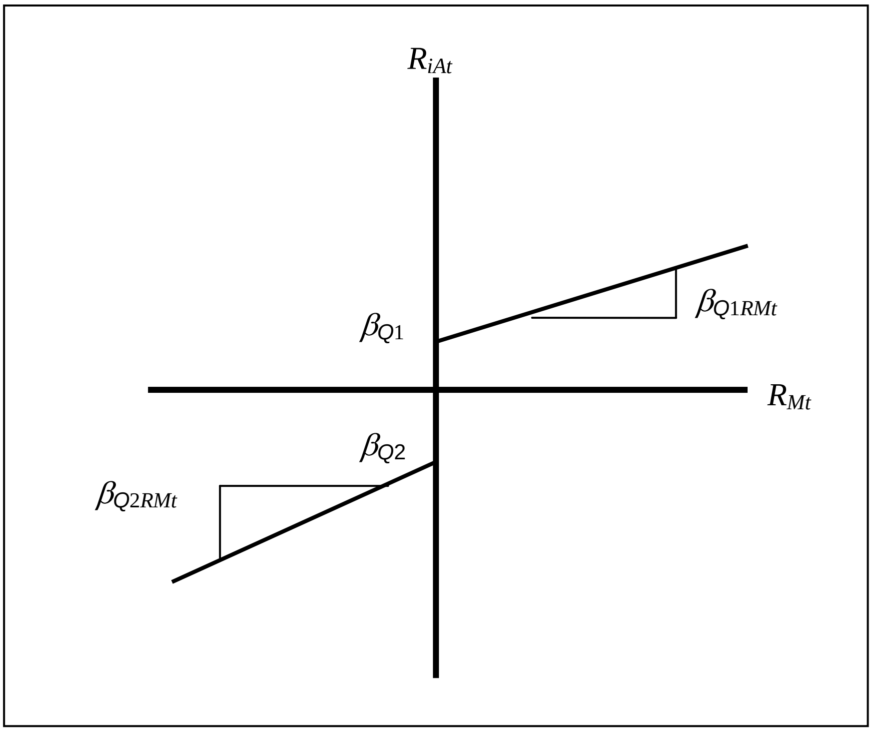


The employment of two fitted lines (where the market model furnishes only one), remains consistent with the concept of market efficiency. It simply shifts focus from measuring abnormal returns from 'returns on average' ($\alpha + \beta R_{Mt}$) to measuring the significance of upticks against positive returns on average, and downticks against negative returns on average, given that in the stock price's general random walk, both positive and negative returns are likely to be common, and not necessarily behave as if there were mirror images of each other. Effectively the model posits that a positive abnormal return must be significantly greater than $\beta_1 Q_1 + \beta_1 Q_1 R_{Mt}$ and a negative abnormal return must be significantly lower than $\beta_2 Q_2 + \beta_2 Q_2 R_{Mt}$. The model makes no prediction as to whether a return will be positive or negative, but quite reasonably assumes in the conducting event studies that the behaviour of both estimation period and test period returns is already known.

2.2.2. 3-state (by Market Index) Model.

The second 3-state model also employs Equation (7). What is different is that it assigns returns to the positive and negative states depending on the sign of the associated return on the market. This makes for quite a different diagram. In Figure 2 there are two intercept terms.[3] Further, a negative market return does not necessarily imply that its matched company return is also going to be negative. The model's fitted line relating to the negative region may be either below, straddling or above the horizontal axis and is unlikely to pass through the origin.

Figure 2: 3-state (by Market Index) Model



2.2.3. 4-state Model.

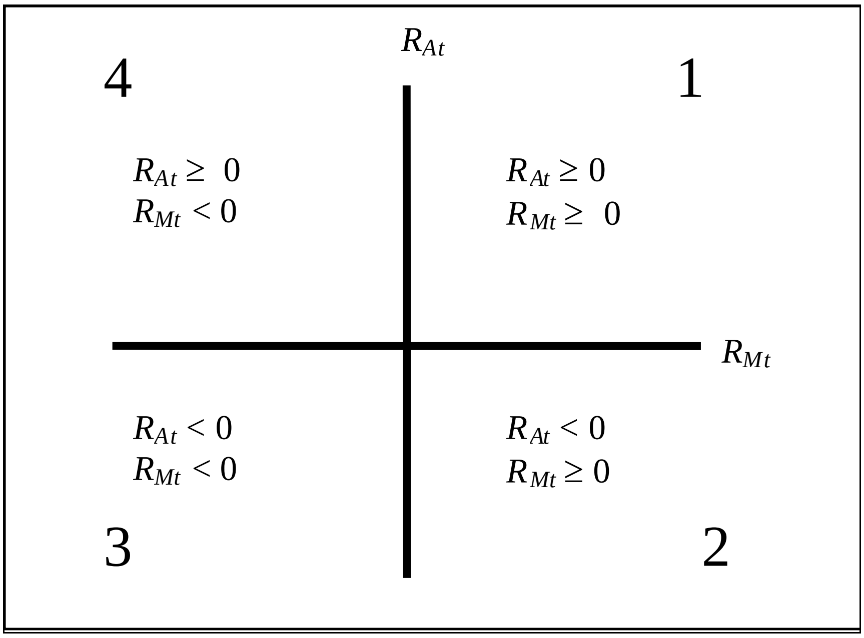
Norsworthy et al (2004) develop a 4-state model by using both the horizontal and vertical axes to partition time-series data into four quadrants by the combination of signs of the company return and matched market return. With this additional information coding, the daily return on company 'A' becomes R_{iAt} where, in the t^{th} instance, the return falls into quadrant i. The four quadrants are labelled in Figure 3.

Again, investors do not know in advance where an observation (R_{iAt}, R_{Mt}) will be recorded relative to the axes. Jokung and Meyfredi (2003, p.3) note the two quadrants in which R_{Mt} is positive are indicative of a rising market, while the other two with a negative R_{Mt} show the market falling (at least over the period of day t). Therefore, it is possible that investors with an eye on price movements will have a sense of whether their intended transaction is likely to

3. However, it is extremely unlikely there will be a market return observation sited precisely on the vertical axis.

be moving with (same signs) the market or (contrary signs) against it. In statistical terms, this is impounded in a much higher R^2 in the regression procedure calculating the expected returns.

Figure 3: Classification of Quadrants used by the 4-state Model.



This regression is run with dummy variables so that, for each of the four quadrants, a unique intercept term (α_{iA}) and also a unique beta β_{iA} are calculated.

$$R_{iAt} = \sum_{i=1}^{4} \alpha_{iA} + \sum_{i=1}^{4} \beta_{iA} R_{Mt} + \varepsilon_i \tag{8}$$

This equation expands to Equation 9 where the dummies (Q_i) take on the value '1' for the i^{th} quadrant, otherwise zero, and $\beta_{iA}Q_i$ (with four states) replaces α_{iA}[4]:

$$\begin{aligned} R_{iAt} = {} & \beta_{1A}Q_1 + \beta_{2A}Q_2 + \beta_{3A}Q_3 + \beta_{4A}Q_4 \\ & + \beta_{5A}Q_1R_{Mt} + \beta_{6A}Q_2R_{Mt} + \beta_{7A}Q_3R_{Mt} + \beta_{8A}Q_4R_{Mt} + \varepsilon_t \end{aligned} \tag{9}$$

For each day of an event study's test period, an abnormal return would be generated by subtracting the right-hand side (excluding the error term) of Equation 9 from the day's

[4] Note that the subscript '*i*' is not carried through for the independent variable, R_{Mt} in either this or the immediately preceding equation. This is because the observation has already been assigned with respect to the company share return in conjunction with it per the decision table embedded in Figure 3.

observed return – just as for the market model, but with the value of the dummies always ensuring that only one pair of slope and intercept coefficients will be switched on while the other three are switched off.

3. Data and Preliminary Analysis.

The initial data set was originally collected for a joint earnings-and-dividend announcement study. The set consists of 948 events between April 1990 and December 1999 where companies listed on the New Zealand Stock Exchange announced dividend-and-earnings news. Adjusted closing-price series, the value-weighted NZX Gross All Companies Index, announcement dates, and also earnings per share and dividend-per-share information were all provided by the Investment Research Group Ltd, a New Zealand financial data archive. Each announcement event had to have daily price data available from at least 111 days before till at least 10 days after the day of the event. These data sets comprise the population of 1990s New Zealand observations of this sort of news event with test periods free of extraneous announcement phenomena.

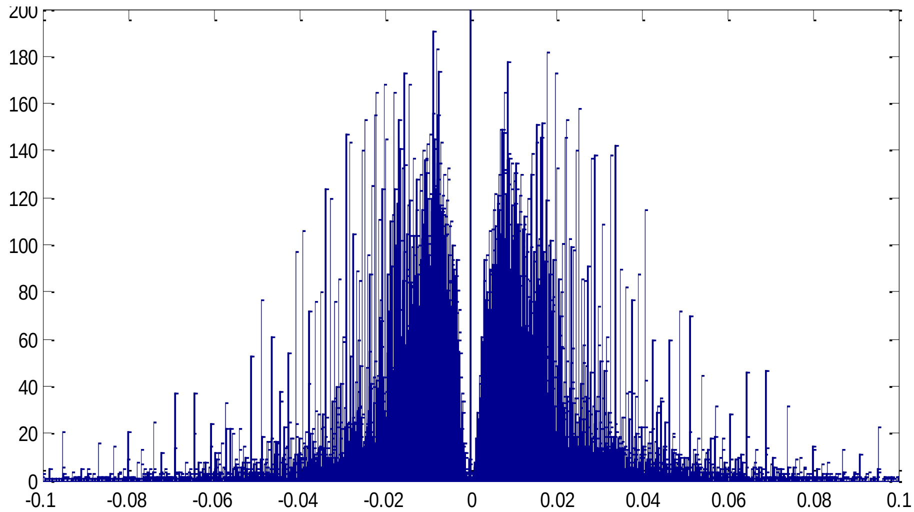
The trading frequency characteristics are interesting and salient in both the estimation periods and the test periods of the 948 data sets. While 211 have estimation periods in which trading occurred every day, the sample tails down to five instances in which the estimation period furnished less than 10 actual days of trading. With respect to the day of the event, t_0, 847 recorded trades and 101 (or just under 11%) did not. These 101 instances of failure to trade on day zero amount to 37.13% of 272 zero-value returns that were recorded on the day of the announcement event.

However, if the event window is redefined as a three-day span, then the number of traders rises to 910 (96%) with the remaining 38 being non-traded over the three-day span. However the 910 traders contain 53 instances of zero price change in the span. At the extreme end of the sample's spectrum were four company/event data sets with no trading at all in the 21-day test period (days t_{-10} to t_{+10}).

With respect to the overall incidence of zero-value returns, it is recognised that they can be the result of either an absence of trading activity or from liquidity trading that fails to shift the price. Failure to trade can be diagnosed from observing that the daily trading volume is also zero. The percentage of zero-value returns that are due to no trading (from all 121 available days from the estimation period and the test period combined) is 59.62%.

Frequent absence of trades over stretches of time inside the Market Model estimation period is strongly likely to give rise to daily returns that are not normally distributed.

Figure 4: Distribution of Log Returns with Both Axes Truncated.



The default method for handling these absences of trading is to assign each one a zero-value return; but the prevalence of zero-value returns drives the behaviour of the OLS regressions used in Market Model estimation. Figure 4 shows the distribution of returns with the horizontal axis (return value) restricted to –0.1 and +0.1 and the vertical axis (count) cut off at 200. This is a very artificial view because the free-standing spike at zero has a count of 41,655.

Of interest also is the absence of values that are close to zero — which causes the zero-return spike to rise from the bottom of a deep valley. This implies that the returns change in discrete steps relating to the price changes in dollars and cents on a share; and that there is a minimum tick-size.

Initially, 948 data sets are available with respect to the market model; but this number is reduced to provide identical input data in the assessment of all of the competing models. The 4-state model is capable of processing 801 data sets, while the 2-state model handles 938 of the data sets. In the middle ground between these, the 3-state (by company) model is able to process 900, and the 3-state (by market) can be used on 906 data sets. The final usable data is 794. This is a result of the processing requirements of an alternative 4-state model that was dropped.[5] Four of the dropped data sets are furnishers of trades on every day of the 100-day trading period. This drops that subset from 211 data sets to 207.

4. Results concerning Expected Returns.

Initially the various models are compared and contrasted on the available data sets. Subsection 5 focuses on regression output evidence from the state models versus market model, while 5.a. partitions the data sets into bands of trading frequency and shows how the 3-state (by company) model outperforms the market model and other methods in terms of desirable regression output statistics and incidence of normality in residuals when trading becomes increasingly thinner.

5. The Regression Output.

To determine how well the various state models perform relative to the market model benchmark, the first items to consider are the mean values of the models' parameters. The two panels of Table 1 deal with the regression results for the 2-state model, the two 3-state models and the 4-state model. Table 2 shows the rates at which parameters are found to have acceptably low rates of a Type I error using a 5% benchmark. These two tables include market model information from above for convenience.

Consider the R^2 information in the third row of Panel A in Table 1. The market model furnishes the lowest R^2 (0.1078) while those of the 2-state model and the 3-state model partitioned by market index are slightly higher (0.1409 and 0.1724 respectively). However, the 3-state model partitioned by company returns has an R^2 (0.7004) that is almost seven times larger than that of the market model This 3-state model also furnishes the highest mean *F*-statistic (87.7387), which is, on average, the most strongly significant *F*-stat as well. This suggests that segregating company returns by sign might make this model a better compiler of expected returns. In addition, by segregating zero-value returns into the third 'state' and leaving them out of the expected return calculation, the 3-state model avoids the market model's problem of setting up understated parameters (as pointed out by Scholes and

5 With the dropping of the alternative 4-state model, which employed rotation as described and tested in Norsworthy et al (2004), the feasible uniform set of data sets applicable to all this paper's models rises to 801. Although it is intended that this will be incorporated into the next draft of this paper, it is unlikely that the extra seven sets of observations will make any material difference to the results tabled in this current draft.

Williams (1977) among others) that get used in forecasting spurious levels of abnormal return in an event study's event window.

Interestingly, only one model consistently furnishes intercept coefficients that, on average, yield p-values indicative of a Type I error of less than the benchmark five percent. The p-values of both intercept coefficients for the 3-state (by company) model (0.0003 and 0.0004 respectively) are significant at less than the 1% level of error. The third state of the 4-state model produces an intercept coefficient with a 4% level of error while no other intercept coefficient of any other model meets the 5% benchmark.

However, the explanatory power of the individual slope coefficients in Panel B is uniformly low. Neither the market model nor any other model manages to achieve significance within any acceptable benchmark level for a Type 1 error. In this instance, the 2-state model has the least unacceptable Type I error (12.78%), with the market model coming in second with a 17.41% error. All of the slope coefficients for the remaining state asset pricing models have p-values that range from just under 25% to 55%.

The actual incidence of acceptable Type I errors for each of the models is reported in Table 2. Of strong interest here is the extremely high incidence of acceptable Type I errors associated with the intercept terms of the3-state (by company) model (99.75%). The only other instances of high incidence rates are furnished by the 4-state model intercepts. In the case of the 4-state model, the high rate may possibly have occurred because two of the four states have had zero-value company returns segregated out of them. In the case of the 3-state (by company) model the reason is clearly because the zero-value company returns that have diminished the fitted line of the market model (in accordance with Scholes and Williams' (1977)) do not diminish the fitted lines for positive returns and negative returns. By contrast, the relatively low incidence of acceptable Type I errors associated with the 2-state model (13.22%) captures the effect of the removal of zero-value company returns while still permitting negative returns to diminish the influence of positive returns. The fact that the 3-state (by market) model furnishes a low incidence of acceptable errors relative to the 3-state (by company) model is indicative of there being both positive and negative company returns in both this model's positive and negative states – which have a dampening effect within each of the states.

With respect to the incidence of Type I errors in slope coefficients, the market model's single slope coefficient (57.93%) outperforms all coefficients furnished by the 3-state and 4-state models. However, the superior incidence of an acceptable Type I error in the single slope coefficient of the 2-state model (67.63%) is evidence of the effect of removing the influence of zero-value returns, ceteris paribus.

Table 1: Summary Results for all Models.

Panel A: Means and Standard Deviations of Model Regression Statistics and Intercept Coefficients										
	Market Model		**2-state Model**		**3-state Model by Company**		**3-state Model by Market**		**4-state**	
	Mean	**St Dev**	**Mean**	**St Dev**	**Mean**	**St Dev**	**Mean**	**St Dev**	**Mean**	**St Dev**
No. of Data Sets	**794**		**794**		**794**		**794**		**794**	
F	16.2165	29.5506	21.4846	33.412	87.7387	49.1672	8.5811	11.6208	17.3968	9.1543
Sig. F	0.174	0.264	0.0819	0.1658	0	0.0009	0.086	0.1756	0.0003	0.0049
R^2	0.1078	0.1395	0.1409	0.1476	0.7004	0.0975	0.1724	0.1455	0.5417	0.1056
Adj. R^2	0.0987	0.1409	0.1322	0.1491	0.691	0.1005	0.1465	0.1501	0.5068	0.1137
Variance	0.0005	0.0012	0.0005	0.0012	0.0002	0.0011	0.0004	0.0012	0.0003	0.0011
$\beta_{Q1}{}^{*}$	0	0.002	0	0.0036	0.0205	0.0106	0.0003	0.008	0.0077	0.0054
t-Stat	0.0408	0.9842	0.0476	1.2804	9.7403	3.014	0.0941	1.3492	2.2504	1.2621
p-Value	0.4998	0.2879	0.4183	0.303	0.0003	0.0051	0.4099	0.2993	0.1281	0.2091
$\beta_{Q2}{}^{**}$					-0.0193	0.0098	0.0005	0.0101	-0.0186	0.0141
t-Stat					-9.6178	2.9402	0.0841	1.3783	-2.8471	1.2421
p-Value					0.0004	0.0061	0.4134	0.3088	0.0625	0.138
β_{Q3}									-0.0179	0.0127
t-Stat									-3.2321	1.3877
p-Value									0.0433	0.1181
β_{Q4}									0.0081	0.0056
t-Stat									1.9253	0.9399
p-Value									0.1474	0.1984

Panel B: Means and Standard Deviations of Model Slope Coefficients

	Market Model		2-state Model		3-state Model by Company		3-state Model by Market		Unrotated 4-state	
	Mean	**St Dev**	**Mean**	**St Dev**	**Mean**	**St Dev**	**Mean**	**St Dev**	**Mean**	**St Dev**
β_{Q1RMt}^{*}	0.5305	0.4313	0.7353	0.6052	0.2784	0.5063	0.6846	1.1967	0.4127	0.6048
t-Stat	2.9486	2.7445	3.4477	2.9565	1.5185	2.2021	1.5616	1.9982	1.4389	2.0252
p-Value	0.1741	0.264	0.1278	0.2348	0.2654	0.3006	0.2477	0.2957	0.3296	0.3213
β_{Q2RMt}^{**}					0.2121	0.4994	0.7963	1.3469	-0.0035	1.619
t-Stat					1.3119	2.5697	1.7074	2.1014	-0.0168	0.9867
p-Value					0.3255	0.3183	0.2547	0.2954	0.5528	0.2891
β_{Q3RMt}									0.3682	1.2273
t-Stat									1.075	2.1985
p-Value									0.4062	0.3306
β_{Q4RMt}									0.1476	0.6442
t-Stat									0.2425	0.8792
p-Value									0.5391	0.2769
Zero Region?	**NO**		**NO**		**YES**		**YES**		**NO**	

The means and standard deviations for all coefficients generated on all five models are lined up in this table. The input data is 948 100-day estimation period data sets of NZX-listed company log returns and matched market index log returns (from between early 1990 and December 1999). The market model processes all of these. However, the requirement that each state of the state models must contain a minimum of 6 observations for successful processing reduces the number of eligible data sets as the number of states grows. The number of datasets able to run all five models is only 794. However, the 3-state model (by company) is able to use 900 while the 4-state model is able to use 801. The four states of the 4-state model are explained in Figure 1. The 3-state model (by market) partitions company returns by whether the matched market return is positive or negative and quarrantines zero-value company returns in a zero region. The 3-state model (by company) partitions company returns by whether it is positive or negative and quarrantines zero-value company returns in a zero region.

* The intercept (Panel A) and slope (Panel B) for first quadrant observations in the 4-state model but the sole intercept (slope in Panel B) for the market model ($b_{Q1} = b_{A0}$, $\beta_{Q1RMt} = \beta_{A1}$) and the intercept when market returns are positive in the 3-state model (by market), and the intercept when company returns are positive in the 3-state model (by company).

** the intercept (Panel A) and slope (Panel B) for second quadrant observations in the 4-state model; and the intercept or slope (depending on panel) when market returns are negative in the 3-state model (by market), or when company returns are negative in the 3-state model (by company).

20

Table 2: Incidence of Coefficients with Type I Errors of 5% or less.

Coefficents by Type	Market Model		2-state Model		3-state Model by Company		3-state Model by Market		4-state	
	N	%	N	%	N	%	N	%	N	%
Intercept										
β_{Q1}	33	4.16%	105	13.22%	792	99.75%	110	13.85%	462	58.19%
β_{Q2}					792	99.75%	118	14.86%	604	76.07%
β_{Q3}									654	82.37%
β_{Q4}									366	46.10%
Slope										
β_{Q1RMt}	460	57.93%	537	67.63%	298	37.53%	327	41.18%	242	30.48%
β_{Q2RMt}					233	29.35%	312	39.29%	40	5.04%
β_{Q3RMt}									182	22.92%
β_{Q4RMt}									23	2.90%
No. of Data Sets	794		794		794		794		794	

This table provides, for each model, the incidence of parameters that furnsih a Type I error of no greater than 5%. The row headings are the quartile designations for the 4-state model. Because the market model has only one intercept and one slope coefficient, it is slotted for convenience, into the first quadrant rows. Similarly, the various state asset pricing models have intercept and slope coefficients slotted into the first two quadrant rows. N is the number of data sets (out of 794) that furnish a Type I error within the 5% benchmark and this is accompanied by its incidence in percentage terms.

a. Trading Thinness and Normality Tests.

Table 3 presents normality test results on the residuals from the models. The market model results are furnished in the two columns labelled MM.[6] The patterns furnished by the Jarque-Bera and Lilliefors Tests are similar, with the Lilliefors figures tending to be higher for the 3-state models, while slightly more conservative for the market model and 2-state model. Therefore the Jarque-Bera results will be discussed, with the Lilliefors findings mostly left in a corroborative role.

In Panel A, which where the two tests were performed on the full sample for each methodology, all of the state models except the 4-state perform better than the market model. The 3-state (by company) shows a small improvement at 33.12% over the market model's 26.2%; but the 2-state and 3-state (by market) models both furnish just over a 72% incidence of normality. The Liliefors test, however doubles the market model's incidence of normality (29.56%) in the 3-state (by company) model's case (52.27%). In Panel C, where the top trading band is diced into two ten-day bands (i.e., between 81 and 90 days trading, and between 91 and 100 days) this pattern in each of them. Further, when the 207 full-traded data sets are considered in isolation, the 2- and 3-state (by market) models produce close to double the incidence of normality (67.15% and 68.60%) found in the market model's 42.03%, while the 3-state (by company) model dips to only 29.95% normality. However, the Liliefors test rates the 3-state (by company) model at marginally more normally distributed than the market model by just under half a percentage point (53.62% versus 53.14%).

For every band in Panel B, the number of datasets with normally distributed residuals is furnished for each model along with the model's incidence of normality in that trading range. On 636 data sets in the most heavily-traded band (81-100 days) the market model achieves a 32.39% incidence. This drops to 28.62% for the 3-state (by company) model while remaining at 70.75 for the 2-state and 3-state (by market) models. The Liliefors test, again however, furnishes evidence in favour of the 3-state (by company) model with a 49.21% rate of normality versus the market model's 29.56%.

6. Please note that there are minor differences between the MM figures in the two tables that are

Table 3: Normality Tests on Model Residuals.

	JARQUE-BERA					LILLIEFORS				
Band	MM	2-State	3-State by Co	3-State by Mkt	4-State	MM	2-State	3-State by Co	3-State by Mkt	4-State
Panel A: Full sample										
0 - 100	26.20%	72.29%	33.12%	72.67%	22.92%	23.68%	69.77%	52.27%	70.15%	26.83%
(Obs)	208	574	263	577	182	188	554	415	557	213
Panel B: Partitioning by 20-day bands										
81 - 100	32.39%	70.75%	28.62%	70.75%	18.87%	29.56%	68.71%	49.21%	67.61%	24.53%
(Obs)	206	450	182	450	120	188	437	313	430	156
61 - 80	1.69%	78.81%	46.61%	81.36%	33.05%	0.00%	74.58%	62.71%	79.66%	33.90%
(Obs)	2	93	55	96	39	0	88	74	94	40
41 - 60	0%	77.14%	65.71%	77.14%	54.29%	0%	74.29%	68.57%	80.00%	40.00%
(Obs)	0	27	23	27	19	0	26	24	28	14
21- 40	0%	80.00%	60.00%	80.00%	80.00%	0%	60.00%	80.00%	100.00%	60.00%
(Obs)	0	4	3	4	4	0	3	4	5	3
0 - 20										
(Obs)										
Panel C: More than 80 days traded										
91 - 100	35.42%	70.65%	27.59%	70.84%	18.59%	34.44%	70.45%	51.08%	68.30%	25.44%
(Obs)	175	355	135	356	89	170	354	255	343	124
81 - 90	20.00%	71.20%	32.80%	70.40%	20.00%	9.60%	61.60%	41.60%	64.80%	20.80%
(Obs)	25	89	41	88	25	12	77	52	81	26
Panel D: Trading every day of the 100-day estimation period										
100	42.03%	67.15%	29.95%	68.60%	21.26%	53.14%	74.40%	53.62%	65.70%	33.82%
(Obs)	87	139	62	142	44	110	154	111	136	70

The incidence of normality in the event-study estimation-period residuals calculated from four versions of state asset pricing models are tabulated alongside that of the market model (MM) with respect to the Jarque-bera Test and the Lilliefors Test. The estimation period was set at 100 days in length and contained all available daily company returns and their associated returns on the value-weighted NZX All Companies Index. The Jarque-bera and Lilliefors Tests for normality are both set up to detect departures from normality. The table furnishes the incidence of normality directly by reporting the incidence of failure to detect non-normality at a 5% level of error. All data sets are from firms listed on the NZX that happened to make joint dividend and earnings announcements falling between April 1990 and the end of December 1999 and whose date of trading commencement on the Exchange enabled them to furnish a 100-day estimation period.

The percentages (and observations) in each column show the proportion (number) of observations in a band that are normal in that band for that model. The total number of datasets is 794. The total number processed at each level of trading thinness is shown in Table 7 for each band for each model.

23

With respect to all more thinly traded bands, the Jarque-Bera incidences of normality for the all of the state models climb, while those for the market model drop towards (and then to) zero. In the 41-60 trading days band, for instance, there are 35 data sets but for the market model the incidence of normality is zero. By contrast, the 3-state (by company) model achieves an incidence of 65.71, while the 2-state and 3-state (by market) register just over 77% each. The 4-state model continues to perform more poorly, registering a 39% incidence of normality in this instance. And, although there are only 5 data sets in the 21-40 trading day bracket, the market model's zero incidence of normality is in stark contrast to the 3-state model's 60% incidence and an 80% incidence over all of the other three state asset pricing models.

In Table 4 the pattern evident in Table 3 is repeated. The mean kurtosis figures for the state asset pricing models run on the full sample of data sets (Panel A) are all lower than the 6.7026 furnished by the market model; but the market model does perform better than the 3-state (by company) and 4-state models when there are 91 or more actual trading days (Panels C and D).[7] On the other hand, where there are 80 or less days of trading, all of the state models furnish lower kurtosis figures than does the market model. However, the 2-state and 3-state (by market) models furnish uniformly lower mean kurtosis figures over all trading bands than do either the market model or the 3-state (by company) model.

With respect to skewness, there is yet again a similar pattern. The 2-state and 3-state (by market) asset pricing models outperform the market model and the 3-state (by company) model over all trading ranges. The 3-state (by company) model only outperforms the market model, however, when the number of days traded drops below 81 days.

In summary, the residuals of the 2-state and 3-state (by market) models conform better to a normal distribution than those of the 3-state (by company) model. This stands in contrast with the superiority of the 3-state (by company) model in terms of the *F*-stat and R^2 values over those for these other models shown in Table 1 back in Section 5. The 4-state model turns out generally to be the worst performer of all of the state asset pricing models examined with respect to incidence of normally distributed residuals. Nevertheless, both of these models outperform the market

7. A normal distribution has a kurtosis of 3.0, while the skewness value will be zero.

Table 4: Kurtosis and Skewness of Residuals.

	Average Kurtosis					Average Skewness				
	MM	2-State	3-State by Co	3-State by Mkt	4-State	MM	2-State	3-State by Co	3-State by Mkt	4-State
Band										
Panel A: Full sample										
0 - 100	6.7026	4.0717	6.5816	4.0169	7.1649	0.2182	0.1528	0.2667	0.1447	0.4334
(Obs)	794	794	794	794	794	794	794	794	794	794
Panel B: Partitioning by 20-day bands										
81 - 100	6.1122	4.1924	6.8787	4.1433	7.4539	0.2286	0.1594	0.3057	0.1496	0.4408
(Obs)	636	636	636	636	636	636	636	636	636	636
61 - 80	8.0425	3.4760	5.3684	3.3837	6.0973	0.3254	0.1835	0.2694	0.1651	0.5072
(Obs)	118	118	118	118	118	118	118	118	118	118
41 - 60	11.9765	4.0423	5.5841	3.9423	5.8627	-0.4066	-0.1045	-0.3950	-0.0513	0.0230
(Obs)	35	35	35	35	35	35	35	35	35	35
21- 40	13.2684	2.9801	4.3973	3.4126	4.7111	0.7373	0.3947	-0.1267	0.4185	0.6291
(Obs)	5	5	5	5	5	5	5	5	5	5
0 - 20										
(Obs)										
Panel C: More than 80 days traded										
91 - 100	5.7664	4.1759	6.8260	4.1357	7.3939	0.2343	0.1624	0.3025	0.1522	0.4299
(Obs)	511	511	511	511	511	511	511	511	511	511
81 - 90	7.5256	4.2600	7.0942	4.1742	7.6992	0.2051	0.1472	0.3187	0.1390	0.4855
(Obs)	125	125	125	125	125	125	125	125	125	125
Panel D: Trading every day of the 100-day estimation period										
100	5.5355	4.3481	6.9479	4.2948	7.3973	0.2396	0.1857	0.3533	0.1654	0.4231
(Obs)	207	207	207	207	207	207	207	207	207	207

The average kurtosis and skewness in the event-study estimation-period residuals calculated from four versions of state asset pricing models are tabulated alongside that of the market model (MM). The estimation period was set at 100 days in length and contained all available daily company returns and their associated returns on the value-weighted NZX All Companies Index. All data sets are from firms listed on the NZX that happened to make joint dividend and earnings announcements falling between April 1990 and the end of December 1999 and whose date of trading commencement on the Exchange enabled them to furnish a 100-day estimation period.

The upper figure in each row is kurtosis (left half) and skewness (right half) for the given band of the model in that column. The total number of data sets (observations) is 794. The total number processed at each level of trading thinness for each band for each model is shown as the lower figure in each row.

25

model on the normality criterion when trading occurs on less than 81 days. It is clear then, that state models perform better than the market model as the number of trading days in an event study expected-return estimation period tails off.

6. Conclusions.

The paper has focused on the role of zero-value company returns in the problem of accounting for missing trades in data sets when stocks are thinly traded. Although zero-value returns may result from liquidity trading, they are especially likely to be the result of no trading taking place when rafts of zero-value returns occur over extended periods of time. Failure to trade is very common for the stocks of smaller firms on stock exchanges everywhere. In this paper, 59.62% of the zero-value returns were instances of absence of trading.

This paper applied a 2-state, two 3-state and a 4-state model to the task of compiling expected returns for use in an event study context. Of particular importance was the question – would they offer an improvement over the market model with respect to event study data sets from markets with thin trading? A portfolio of 948 New Zealand data sets associated with 1990s dividend-and-earnings announcement events provided the raw material. An important point was that the estimation period was restricted to a standard 100 days, which is a common length for studies of events that recur twice yearly.

In Section 4, the data were reduced to 794 sets of time series observations in order to test all models on identical inputs. The best model for event study purposes turned out to be the 3-state (by company) model. The adoption of three states — negative, positive and zero — caused two things to happen. First, the mean *F*-statistic and adjusted R^2 values increased over both the market model and the 4-state model. Second, the segregation of zero-value returns from both 3-state models' regressions turned out to be doubly advantageous. With these segregated out, they could no longer furnish spurious abnormal returns (potentially of various sizes and statistical significance) and instead, the associated abnormal return was free to be assigned a zero value for event-related hypothesis testing. In addition, the 3-state (by company) model's residuals (by Liliefors test evidence although not by Jarque-bera Test evidence) tended to be normally distributed more often and to a greater degree than those of the market model.

The paper then went on to use abnormal returns generated by the 3-state (by company) model and the market model in a restricted least squares regression procedure to determine the presence or not of a dividend signal or an earnings signal. The two sets of abnormal returns furnished broadly similar findings in favour of these signals being present. The market model's evidence was stronger, but may have been overstated as a result of its handling of zero-value returns. This overstatement is not present in the findings associated with abnormal returns furnished by the 3-state (by company) model.

Further, while the market model was able to handle all 948 data sets (albeit with some poor regression output characteristics), the 3-state (by company) model was able to handle almost 90 percent (850) of them. The limiting factor was that each category of return was required to contain a minimum of six observations before the procedure would run. However, this loss in available data is quite small.

The most important contribution this paper makes is that it shows all models employing dummy variables governing the sign of company returns outperform the market model, on the normality criterion, once the number of days traded drops below 81 days in a 100-day estimation period. Of these, the 3-state (by company) model provides the best fit with the data in terms of R^2 and regression *F*-statistics. This is a preferable alternative to the market model for use in event studies run on data where trading is likely to be thin.

Appendix:
Application to joint Earnings and Dividend Announcement.

The 3-state (by company) model and the market model (modified by the lumped method) will now furnish, abnormal returns for use in the detection of a possible dividend or earnings signalling effect, or the possible significant influence of an interaction between these two items. Given that in New Zealand and a number of other countries, dividends and earnings are announced simultaneously, the paper uses the restricted least squares methodology of Kane, Lee and Marcus (1984) to determine the existence of significant linkages between these joint news items and the nature of the abnormal returns generated by the market model and the best of the state models – the three-state (by company) model. The restricted least squares methodology was also used by Easton (1991) and Lonie, Abeyratna, Power and Sinclair (1996). Its purpose is to sort out the interaction effects of joint dividend and earnings announcements.

In this procedure the dependent variable is the abnormal return on day zero (AR_{t0}). There are two categories of independent variables. The first-order variables are scaled measures of change in dividend and change in earnings.[8] The second category consists of dummy variables which capture the interaction effects between the first-order variables. Of the nine possible permutations of changes in direction of announced DPS and announced EPS, the six that make economic sense are:

DI-EI	Dividend increases with earnings also increasing (good news case);
DD-EI	Dividend down with earnings increasing ;
DI-ED	Dividend increasing with earnings down;
DNC-EI	No change in dividend while earnings increase;
DNC-ED	No change in dividend while earnings go down;
DD-ED	The dividend and earnings both decline (bad news case).

[8] Because the inclusion of dividend initiations means that a simple percentage change in dividend from one year earlier would yield infinite value, the measure of change for both DPS and EPS variables is: $\frac{x_{HALF-YEAR\,t} - x_{HALF-YEAR\,t-1}}{P_{DAY\,t-1}}$, where t, whether measuring half-years or days, is the period ending at the close of trade on day zero.

Five of these DPS-EPS directional combinations are represented by dummies, with the bad-news case, DD-ED being left to be represented by the intercept term. A priori, we would expect the good-news and bad-news cases (first and last above) to be associated with a greater shift in the size of AR_{t0} than in the remaining four cases where the two news items could be expected to dampen each other. The formal structure of the restricted least squares model is as follows:

$$\begin{aligned}
(i)\quad & AR_{t0} = \alpha + \beta_1 \Delta DPS + \beta_2 \Delta EPS + \beta_3 D_1 + \beta_4 D_2 \\
& \qquad\qquad + \beta_5 D_3 + \beta_6 D_4 + \beta_7 D_5 \\
(ii)\quad & AR_{t0} = \alpha + \beta_1 \Delta DPS + \beta_2 \Delta EPS \\
(iii)\quad & AR_{t0} = \alpha + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + \beta_4 D_4 + \beta_5 D_5
\end{aligned} \tag{10}$$

In this set of three linked equations, the good-news combination (DI-EI) is represented by D_1, and the dummies D_2 to D_5 model the remaining four combinations in the order listed above.

The first of the three regression runs is an unrestricted regression containing all of the independent variables, while the other two contain restrictions. In regression (ii) the interaction dummies are left out, while regression (iii) is restricted to just being run on the dummies alone. The joint significance of the first order variables is measured by a first-order *F*-statistic calculated from the residual sums of squares of regressions (i) and (iii):

$$F_{FIRST\ ORDER} = \frac{\left(\dfrac{RSS_{RESTRICTED(EQN(iii))} - RSS_{UNRESTRICTED}}{m_{EQN(iii)}} \right)}{\left(\dfrac{RSS_{UNRESTRICTED}}{(N-K)} \right)} \tag{11}$$

In this formulation, m is the degrees of freedom associated with regressors omitted from equation (iii), N the number of observations and K the number of degrees of freedom lost in the unrestricted regression. The joint significance of the interaction variables is similarly measured from the residual sums of squares from regressions (i) and (ii):

$$F_{INTERACTION} = \frac{\left(\dfrac{RSS_{RESTRICTED(EQN(ii))} - RSS_{UNRESTRICTED}}{m_{EQN(ii)}} \right)}{\left(\dfrac{RSS_{UNRESTRICTED}}{(N-K)} \right)} \tag{12}$$

This approach to testing for significance is not proposed as being, in any way, superior to the Corrado rank test used by Maynes and Rumsey (1993). It is merely an off-the-shelf methodology that addresses the special case of simultaneous news items, which the rank test does not.

Table 5 and Table 6 furnish results generated by the restricted least squares regression procedure. The effective result is the same in both tables. In

Table 5, the behaviour of day zero abnormal returns furnished by the market model (the dependent variable) is associated with both change in DPS (p-value 0.000) and change in EPS (p-value 0.0412); and this is backed up by a strongly significant first-order *F*-statistic (p-value 0.0004). Table 6 furnishes an almost identical result with respect to the association of ΔEPS (p-value 0.0000) and ΔDPS (p-value 0.0008)with day zero abnormal returns furnished by the 3-state (by company) model.

Again the first-order *F*-statistic is strongly significant (p-value 0.0001). However, the evidence concerning the strength of association between paired earnings-and-dividend changes and day zero abnormal returns is more muted when the abnormal returns are provided by the 3-state model. In Table 6, the interaction *F*-statistic is only weakly significant (p-value 0.0647) whereas in

Table 5 with market model abnormal returns, it remains strongly significant (p-value 0.0001). It is clear then, that the results are broadly similar, but use of the 3-state (by company) model's abnormal returns leads to a more conservative result. Both tables furnish evidence in favour of there being dividend and earnings signals present, but it is slightly weaker evidence when the 3-state model furnishes the dependent variable. This is no bad outcome, given the more robust characteristics of this 3-state model shown in the preceding sections of this paper.

Table 5:
Restricted Least Squares Regression employing Day Zero Abnormal Returns generated by the Market Model.

Panel A: Unrestricted Regression (EQN (i))							
	Beta	SE	t-Stat	p-Value			
Intercept	-0.0168	0.0057	-2.9583	0.0032		**N**	948
ΔDPS	0.0021	0.0006	3.7595	0.0002		**DF**	940
ΔEPS	0.0003	0.0004	0.7864	0.4318		**R^2**	0.0874
DI-EI	0.0334	0.0076	4.4238	0.0000		**F Stat**	12.8590
DD-EI	0.0118	0.0121	0.9779	0.3284		**p value**	0.0000
DI-ED	0.0222	0.0095	2.3276	0.0201		**σ^2**	0.0044
DNC-EI	0.0173	0.0080	2.1604	0.0310			
DNC-ED	0.0068	0.0073	0.9344	0.3504			

Panel B: Restricted Regression (EQN (ii)) First order variables only (948 Observations)							
	Beta	SE	t-Stat	p-Value			
						N	948
Intercept	0.0007	0.0022	0.3246	0.7455		**DF**	945
ΔDPS	0.0034	0.0005	6.8133	0.0000		**R^2**	0.0624
ΔEPS	0.0007	0.0003	2.0442	0.0412		**F Stat**	31.4410
						p value	0.0000
						σ^2	0.0045

Panel C: Restricted Regression (EQN (iii)) Dummy variables only							
	Beta	SE	t-Stat	p-Value			
Intercept	-0.0269	0.0050	-5.4230	0.0000		**N**	948
DI-EI	0.0499	0.0063	7.9789	0.0000		**DF**	942
DD-EI	0.0154	0.0119	1.2894	0.1976		**R^2**	0.0721
DI-ED	0.0356	0.0090	3.9592	0.0001		**F Stat**	14.6350
DNC-EI	0.0276	0.0075	3.6659	0.0003		**p value**	0.0000
DNC-ED	0.0164	0.0069	2.3850	0.0173		**σ^2**	0.0045

Panel D: Restricted Least Squares *F*-statistics :						
		Crit. Val. 5%		Crit.Val. 1%		p-Value
$F_{\text{FIRST ORDER}}$	7.8772		3.0053	4.6278		0.0004
$F_{\text{INTERACTION}}$	5.1490		2.2236	3.0367		0.0001

This table furnishes evidence supporting the presence of a dividend signal and also an earnings signal. ΔDPS is change in dividend per share. ΔEPS is change in earnings per share. DI, DD and DNC are increase, decrease and no change in dividend. EI and ED are increase and decrease in earnings; and the hyphen indicates linkage. The strongly significant first-order *F*-statistic indicates that the behaviour of the two first order variables is associated with the behaviour of the dependent variable (abnormal return on day zero). The strongly significant interaction *F*-statistic indicates that interactions between earnings change and dividend change also have a close association with the behaviour of the dependent variable.

Table 6:
Restricted Least Square Regression employing Day Zero Abnormal Returns generated by the 3-state (by Company) Model.

Panel A: Unrestricted Regression (EQN (i)) on 850 observations.							
	Beta	**SE**	**t-Stat**	**p-Value**			
Intercept	-0.00567	0.003599	-1.57498	0.115636		**N**	850
ΔDPS	0.000633	0.000498	1.272062	0.203702		**DF**	842
ΔEPS	0.000808	0.000208	3.891605	0.000107		**R^2**	0.0658
DI-EI	0.0122	0.004786	2.549013	0.010979		**F Stat**	8.4739
DD-EI	0.000308	0.007083	0.043499	0.965314		**p value**	0.0000
DI-ED	0.005742	0.005965	0.962563	0.336043		**σ^2**	0.0014
DNC-EI	0.007574	0.004952	1.529594	0.126493			
DNC-ED	0.001662	0.004516	0.367985	0.712977			

Panel B: Restricted Regression (EQN (ii)) First order variables only							
	Beta	**SE**	**t-Stat**	**p-Value**			
						N	850
Intercept	0.0004	0.0013	0.3201	0.7490		**DF**	847
ΔDPS	0.0013	0.0004	3.3487	0.0008		**R^2**	0.054226
ΔEPS	0.0009	0.0002	4.5382	0.0000		**F Stat**	24.2815
						p value	5.57E-11
						σ^2	0.001423

Panel C: Restricted Regression (EQN (iii)) Dummy variables only							
	Beta	**SE**	**t-Stat**	**p-Value**			
Intercept	-0.0128	0.0030	-4.2939	0.0000		**N**	850
DI-EI	0.0217	0.0038	5.7825	0.0000		**DF**	844
DD-EI	0.0066	0.0070	0.9386	0.3482		**R^2**	0.043798
DI-ED	0.0129	0.0054	2.4138	0.0160		**F Stat**	7.731687
DNC-EI	0.0151	0.0045	3.3309	0.0009		**p value**	4.01E-07
DNC-ED	0.0073	0.0041	1.7678	0.0774		**σ^2**	0.001444

Panel D: Restricted Least Squares *F*-statistics :							
			Crit. Val. 5%		**Crit.Val. 1%**		**p-Value**
$F_{FIRST\ ORDER}$	9.9208		3.0064	4.6304			0.0001
$F_{INTERACTION}$	2.0885		2.2247	3.0390			0.0647

This table furnishes evidence supporting the presence of a dividend signal and also an earnings signal. ΔDPS is change in dividend per share. ΔEPS is change in earnings per share. DI, DD and DNC are increase, decrease and no change in dividend. EI and ED are increase and decrease in earnings; and the hyphen indicates linkage. The strongly significant first-order *F*-statistic indicates that the behaviour of the two first order variables is associated with the behaviour of the dependent variable (abnormal return on day zero). However, the association of dividend-and-earnings directional-change interactions with the dependent variable is more muted, since the interaction *F*-statistic is only weakly significant.

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